Resources Allocation for Large-Scale Dynamic Spectrum Access System Using Particle Filtering

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***Abstract*—This paper proposes an efficient spectrum and power allocation solution for a large scale dynamic spectrum access (DSA) systems. Unlike conventional methods relying on optimization techniques which need huge computational capabilities and full information exchange, in this paper we rely on particle filtering to allocate the available bands among users in a distributed manner. Particle filter is based on the representation of the searched state, bands allocation per user in our case, by a set of particles. The Particle filter has the advantage, with comparison to Kalman-based filters, of its adaptivity to general scenarios (non-linear models, non-Gaussian noise, multi-modal distributions). Like Kalman-based filters, two model equations are needed for particle filter. (i) A state evolution equation to characterize the time evolution of the state. For our case, we derive a prediction equation of the channel allocation from the previous allocation from the channel fading temporal correlation. (ii) An observation equation which relates the observation, the Quality of Service in our case, to the channel allocation (state). This equation will be useful in the weighting and re-sampling phases of the filtering algorithm. The performances are analyzed in terms of the per user achieved throughput. In addition, comparison with performance when Q-learning is employed to show the efficiency of our approach.**

***Index Terms*—dynamic spectrum access, efficient spectrum allocation, distributed algorithms, large-scale systems, particle filtering.**

I. Introduction

Optimal resource allocation has been considered crucial in all communication systems driven by the inherent scarcity nature of these resources as well as the pressing needs for efficient energy use [1]. For instance, the current exponential growth in the wireless devices has called into question the inefficiency of the conventional static spectrum allocation policies which resulted on a resource scarcity problem. Thus, proposing efficient spectrum allocation methods and paradigms has become vital than ever before. Dynamic Spectrum Access (DSA) systems have been proposed to cope with this problem, and hence, to improve the spectrum efficiency.

DSA has recently grasped a lot of interest from the research community to deal with an unprecedented growth in wireless users alongside a resources scarcity problem. In this communication paradigm, a non-licensed set of users, commonly called secondary users, is allowed to access the unused portion of the spectrum, called spectrum holes, left by legacy users, called primary users. Of particular interest, when it comes to handling the massive number of users, is the need for efficient and scalable resources allocation methods suitable for these large-scale systems. In this case, distributed approaches are more appealing than the centralized approaches due to their ability to scale well with the number of users when it comes to computational complexity.

Various methods have been proposed in the literature to enable effective resource allocation in DSA systems ranging from game theoretical and Extended Kalman Filtering [2] to Q-learning [3] and evolutionary algorithms [4]. In [2], the authors proposed an Extended Kalman filtering based adaptive game where the DSA agents jointly decide on their transmission power and track the channels' variations. In [3] the authors proposed a distributed multi-band joint spectrum and power allocation based on learning. However, only quasi-static channels have been taken into consideration. In [4], the authors brought forth evolutionary algorithms for spectrum allocation in DSA systems. This family of stochastic search methods is inspired from the natural selection. The authors proposed three algorithms to allocate a set of bands for a set of users using genetic algorithm, quantum genetic algorithm and particle swarm optimization.

Another possible method that belongs to this family of search algorithms is particle filtering [5]. The core idea of it is to estimate the conditional probability density through the use of the Monte Carlo simulations and the importance sampling techniques. Particle filtering has been applied in different applications ranging from video tracking to localization. In wireless communications, the main conventional applications are blind equalization over frequency selective channels in SISO systems [6] or with multi-antennas systems [7]. Moreover, it was applied to signal detection [8] and joint carrier recovery and channel estimation for OFDM systems over frequency selective fading channels [9]. However, very little to no effort has been put towards applying this technique to resource allocation problems in DSA systems.

With all this in mind, we propose in this paper to use particle filtering for distributed resource allocation in large scale DSA systems. We aim to profit from its high capabilities of tracking real-time systems. We formulate the problem of the spectrum allocation among the different users by taking into consideration the interference among users. We assume that each user operates with a fixed power level and the problem will be to select the "best" operating band for each user. The particle filter tracks the changes over the channels to allow each user to get the highest throughput while minimizing the interference caused to the other users. The achieved performance is compared with that achieved when reinforcement learning is used instead.

The reminder of this paper is organized as follows. In Section II, we start by describing our system model and the communication pattern. In Section III, we provide a comprehensive overview about particle filtering principle and algorithm. In Section IV, we give our problem formulation and show how to solve the formulated problem using particle filtering. In section V, we investigate the performances of the proposed resource allocation methods through some numerical analysis while in Section VI, we draw the conclusions.

II. System Model

We consider a set of n users trying to communicate with their correspondent n receivers over one single band each. The m bands have been declared available by all the users through the use of an accurate multi-band spectrum sensing technique (The spectrum sensing phase is out of the scope of this paper). We assume that the number of users is very high compared the number of the available channels (i.e., $n >> m$). Hence, the users will interfere with each other while trying to achieve their maximum throughput.

In our framework, the fading channel between the a transmitter k and a receiver i is modeled by a p^{th} order Auto-Regressive (AR(p)) process [2]. Thus, at the time episode t the channel impulse response of user $h_{ik}^{(j)}(t)$ is given by

$$h_{ik}^{(j)}(t) = \sum_{l=1}^{p} \alpha_l h_{ik}^{(j)}(t-l) + \beta w_i^{(j)}(t), \tag{1}$$

where $h_{ik}^{(j)}(t-l)$ denotes the channel fading impulse at the time episode $t-l$ for the band j and $\left\{\alpha_l\right\}_{l=1}^{p}$ and β are the AR parameters that could be estimated using the Yule-Walker equations [10] which assumes that $\alpha_l = J_0(2\pi l f_d T_b)$ where J_0 is the zerothorder Bessel function of the first kind, f_d is the maximum Doppler frequency and T_b is the channel coherence time.

By selecting a channel out of the available m channels, the user i at the time slot t will interfere with the other users that have selected the same channel band. Hence, the received Signal to Interference plus Noise Ratio (SINR) when using the j^{th} band could be expressed as

$$\gamma_i^{(j)}(t) = \frac{P_i |h_{ii}^{(j)}(t)|^2}{\sum_{\substack{k=1\\k\neq i}}^{n} a_k^{(j)} P_k |h_{ik}^{(j)}(t)|^2 + N_0 B^{(j)}}. \tag{2}$$

As a result, the achieved throughput will be expressed as

$$R_i(t) = \sum_{j=1}^{m} a_i^{(j)} B^{(j)} \log_2(1+\gamma_i^{(j)}(t)), \tag{3}$$

where $a_i^{(j)}$ is a binary index that illustrates whether the j^{th} channel was selected by user i or not such that $\sum_{j=1}^{m} a_i^{(j)} = 1$ to guarantee that each user selects only one band, $B^{(j)}$ is the j^{th} channel bandwidth, $h_{ik}^{(j)}(t)$ is the j-th channel impulse response from the k^{th} transmitter to the i^{th} receiver, and N_0 is the power spectral density of the noise which is assumed constant overtime and equal for the whole spectrum band. We assume that each user k exchanges with the users with whom he shares the j^{th} channel his transmission power level P_k. Thus, the channel gains can be estimated directly by the receivers. By this way, the exchange overhead is far less than the centralized approach for which all the channel gains between all the users over all the bands are required. Different objectives $\mathcal{O}_i(t)$ could be considered when developing a distributed optimization problem. A first objective for each user is to maximize its intrinsic reward which is defined as his own achieved rate. This is known by the selfish behavior for each user as it acts independently of the other users. In this case, it could be written as

$$\mathcal{O}_i(t) = R_i(t). \tag{4}$$

A second objective function that could be considered is the global reward which is the sum of the achieved rewards of all users. This will lead to a cooperative behavior in order to maximize the total (or equivalently the average) reward of all users. In this case, the objective function is expressed as

$$\mathcal{O}_i(t) = \sum_{k=1}^{n} R_k(t). \tag{5}$$

To guarantee more fairness between the users, we could maximize the minimum achieved throughput between all users. In this case, the objective function to be maximized is expressed as

$$\mathcal{O}_i(t) = \min_{1\leq k\leq n} R_k(t). \tag{6}$$

III. Particle Filter Overview

In this section, we provide an in-depth insight about the principle of particle filtering. The core idea of particle filtering (PF) is to estimate the conditional probability density through the use of the Monte Carlo simulation and the importance sampling techniques [5]. More precisely, it relies on a finite number of samples, called particles, to track the probability density by propagating these particles.

A. Background

Considering the following discrete-time state-space model

$$\begin{aligned} x_t &= f(x_{t-1}, u_t), \\ y_t &= g(x_t, v_t), \end{aligned} \tag{7}$$

where x_t is the state at the time t, y_t is the observation, f is the function that governs the state's change, g is the function that links the actual state to the observation, u_t and v_t are the noise of the state and the observation, respectively. Note that this could be seen as an infinite dimensional hidden Markov chain where the state x_t evolves according to a Markov chain with the transition probability is $\mathbb{P}(x_t|x_{t-1})$. Unlike the classical Kalman filtering and its derivatives, this model describes a general context where criteria like linear systems or Gaussian noise are not required. Hence, particle filtering will lead to more accurate performance in a general scenario where such conditions are not met.

Broadly speaking, the filtering problem consists of estimating the state at time t given all the past observation $y_{0:t} = [y_0, y_1, ..., y_t]$ which could be expressed using the Bayes' rule as

$$\mathbb{P}(x_t|y_{0:t}) = \frac{\mathbb{P}(y_t|x_t)\mathbb{P}(x_t|y_{0:t-1})}{\mathbb{P}(y_t|y_{0:t-1})}, \tag{8}$$

where $\mathbb{P}(x)$ denotes the probability of the event x. As these conditional probabilities are difficult to compute, the idea of particle filtering is to rely on a finite number of samples, called particles, to approximate the conditional density and to emulate its evolution through the propagation of these particles. In this case the conditional probability in (8) could be approximated as

$$\mathbb{P}(x_t|y_{0:t}) \cong \sum_{i=1}^{N} w_t^i \delta(x_t - x_t^i), \tag{9}$$

where $\{x_t^i\}_{i=1}^N$ are the particles or the samples, $\{w_t^i\}_{i=1}^N$ are their correspondent weights, and N is the total number of used samples. The question that arises now is how to draw these particles and how to derive their associated weights.

Basically, perfect sampling lies at the basis of Monte Carlo techniques. It consists of approximating the probability density using a finite number of samples with equal weights. This estimate converges to the exact probability density using the strong law of large numbers. However, the sampling could not be applied to particle filtering because only the transition probabilities and observation probabilities are known. Importance sampling has been introduced to do so. In this case the samples are drawn with respect to an arbitrary importance density $\pi(.|.)$. However, by this way, if a new observation is available, the weights should be recalculated. Hence, recursive importance sampling is more convenient to deduce the new weight from the previous one. This is the basic particle filtering algorithm known as sequential importance sampling.

However, this algorithm suffers from the problem of degeneracy where all the weights except one become close to zero. To deal with this problem, re-sampling is introduced. Re-sampling consists of eliminating the particles with low weights and multiplying the ones with high weights.

B. Algorithm

The resulted algorithm is known as Sequential Importance Sampling with Re-sampling (SISR) which has three main steps that could be summarized as follows: (a) the update of the particle $\{x_0^i\}_{i=1}^N$ according to the importance sampling, (b) the update of the weights $\{w_0^i\}_{i=1}^N$ and (c) the re-sampling.

Note that the choice of the importance density is crucial. A commonly used importance density is

$$\pi(x_t|x_{t-1}) = \mathbb{P}(x_t|x_{t-1}^i). \tag{10}$$

This choice leads to a normalized weight

$$w_t^i \propto \mathbb{P}(y_t|x_t^i), \tag{11}$$

which is very practical. On the other hand, the re-sampling importance density used in practice is the one used in equation (9).

IV. Dynamic Spectrum Allocation using Particle Filtering

In [11], particle filter has been used to solve optimization algorithms using randomization method. Our problem is more challenging as channel gains are varying over time. Thus, we need to enhance the proposed approach by accounting for channels variations using (1). In addition, our distributed formulation of the problem raises a new challenge as the decisions taken by each user will affect the obtained throughput of the other users due to interference among users that happen to select the same band as in (3).

Thus, we formulate our dynamic spectrum allocation problem as a filtering problem as follows

$$\mathbf{a}_i(t) = \mathcal{X}(\mathbf{a}_i(t-1)) + \mathbf{u}(t), \tag{12a}$$

$$\mathcal{O}_i(t) = \Psi(\mathbf{a}(t)) + \mathbf{v}(t), \tag{12b}$$

where $\mathcal{X}(.)$ is the function that describes the state's change, $\Psi(.)$ is the function that links the state $\mathbf{a}_i(t)$ to the objective $\mathcal{O}_i(t)$ while $\mathbf{u}$ and $\mathbf{v}$ are the stochastic noises of the state and the observation models, respectively. The observation function $\Psi(.)$ can be deduced from the relationship between the throughput and the channel allocation matrix (3).

Since the particle filter will be applied in a distributed manner, thus for every user i, the objective function $\mathcal{O}_i(t)$ depends on the channel gain of the direct link as well as the interference channels at time t which are related to the previous realizations of these channels at time $t-1$ according to (1), which will be referred to as $\mathcal{F}$. Also, the objective function depends on the channels selected by all the other users except the user i, which will be denoted as $\mathbf{a}_{-i}(t)$. These two sets of parameters are required to get the new state $\mathbf{a}_i(t)$. Therefore, the function $\mathcal{X}$ describing the state change equation can be written as

$$\mathcal{X}(t) = \arg\max_{\mathbf{a}_i(t)} \mathcal{O}_i(t)|\{\mathbf{a}_{-i}(t) = \mathbf{a}_{-i}(t-1), h(t) = \mathcal{F}(h(t-1))\}. \tag{13}$$

Note that the functions $\mathcal{X}(.)$ and $\Psi(.)$ are non-linear functions which limits the performance of the conventional methods of solving (Kalman filters and its derivatives).

For every user i, each particle will represent a state of the channel allocation $\mathbf{a}_i(t)$. Hence, by applying the same principle of particle filtering discussed in Section III, the importance density will be given as $\mathbf{a}_i(t) = \mathcal{X}(\mathbf{a}_i(t-1))$

$$\pi(\mathbf{a}_i(t)|\mathbf{a}_i(t-1)) = \mathbb{P}(\mathbf{a}_i(t)|\mathbf{a}_i^p(t-1)), \tag{14}$$

where $\mathbf{a}_i^p(t-1)$ is the p^{th} particle for the user i, and hence, the normalized weight is then

$$w_i^k(t) \propto \mathbb{P}(O_i(t)|\mathbf{a}_i^k(t-1)). \tag{15}$$

So, by applying the particle filtering steps, the used algorithm is stated in Algorithm 1.

Algorithm 1 Particle filtering based resource allocation for large-scale DSA system.

INPUT: The power levels per user: $\{P_i\}_{1\leq i\leq n}$.
OUTPUT: The channel selection for every user: $\{\mathbf{a}_i\}_{1\leq i\leq n}$.

Initialization of the weights using uniform distribution.
for all time slot t **do**
  for all DSA user i **do**
1) **Prediction:** compute possible particles using (14);
2) **Decision:** select band of the particle giving highest reward;
3) Start transmission on the selected band;
4) Update channels estimation;
5) **Weighting:** update the weights of the particles using (15);
6) **Re-sampling:** apply re-sampling to avoid degeneracy.
  end for
end for

V. Simulation results

A. System Setup

We consider a large scale DSA system where $n = 100$ users are communicating with their associated $n = 100$ receiver over $m = 10$ available bands. The channels between the transmitter and its correspondent receiver as well as the other receivers is assumed to be Rayleigh fading channel with an average channel gain $\left[\frac{d}{d_{ki}}\right]^{\eta}$ where $d = 1Km$ is a reference distance, d_{ki} is the distance between the i^{th} transmitter and the k^{th} receiver and η is the pathloss exponent that is set to 3. We consider the channels to be a first order ($p = 1$) AR process. We assume the m available bands to have the same bandwidth $B = 6\ MHz$. We set the average gain of the direct channel link to be 3 dB stronger than the average of channel interference gain [2]. The time coherence is chosen to be $T_b = 1\ ms$.

Our simulation setup is in line with the IEEE 802.22 standard where users operates over the range of frequencies between 54 MHz and 862 MHz. We assume the bands to be adjacent such that the carrier frequencies over the 10 bands will be in range of 645 MHz and 755 MHz. The Doppler spread f_d is caused by the mobility of the receiver at a maximum speed $v = 70\ Km/h$. Hence, the channel correlation over time α will falls in the interval $[0.97, 1)$. We assume that each user is using a fixed transmit power $P_i(t) = 3\ dBm$ while the noise spectral density N_0 is set to $-100\ dBm$. For the particle filtering, we use $N = 100$ particles.

B. System performance

In the following, the performance of our proposed spectrum allocation scheme is analyzed in terms of the achieved throughput. In Fig. 1, we show the average achieved throughput with the system setting described earlier using the intrinsic objective function (4). We conclude that particle filtering succeed in each time slot to track the channel changes as well as the best channel. Also, we compare it to the case where the resources are allocated using the Q-learning. Particle filtering gives superior average throughput with comparison with the Q-learning.

In Fig. 2, we compare the performances for the different objective functions described earlier in Section II. We plot the average and standard deviation of the throughput obtained by the different users. We observe that the "sum" objective function (5) allows a better average throughput due to the proportionality between mean and sum functions. On the other hand, the "min" objective function (6) results in a better fairness (lower standard deviation between users) on the price of a loss on the total/average throughput.

In Fig. 3, we compare the performance using intrinsic objective function (4) to the difference objective function which was introduced in [12] and shown to improve performance with Q-learning. This difference objective function aims at maximizing exactly the contribution of the user on the total throughput by using a difference function expressed as:

$$\mathcal{D}_i(t) = \sum_{k=1}^{n} R_k(t) - \sum_{k=1}^{n} \hat{R}_{k,-i}(t), \tag{16}$$

where $\hat{R}^{(j)}_{k,-i}(t)$ represents the received throughput by user k in the event user i is absent. This figure reconfirms the results of [12] and allows to still enhance the proposed spectrum allocation algorithm based on particle filtering by including the difference function as objective.

In Fig. 4, we study the effect of the number of particles employed. This is a key parameter for the particle filtering algorithm as it affects both computational complexity and optimality. In fact, the computational complexity of the algorithm is proportional to the number of particles while we show in this figure the obtained average throughput with different number of particles. We observe that $N = 50$ particles is sufficient for convergence thanks to the Re-sampling step which allows to avoid degeneracy.

VI. Conclusions

This paper presents an efficient particle filter algorithm for a distributed spectrum allocation in large-scale DSA systems. The proposed algorithm uses temporal fading correlation of the channels to predict channel estimation based on previous channel states and uses this for the propagation phase of the spectrum allocation. The weighting is based on the received throughput taken as observation while different objectives are used and compared depending on the system's target. Simulation results show the efficiency of the proposed algorithm with comparison to reinforcement learning algorithms.

VII. Acknowledgment

This work was made possible by NPRP grant # NPRP 5-319-2-121 from the Qatar National Research Fund (a member of Qatar Foundation). The statements made herein are solely the responsibility of the authors.

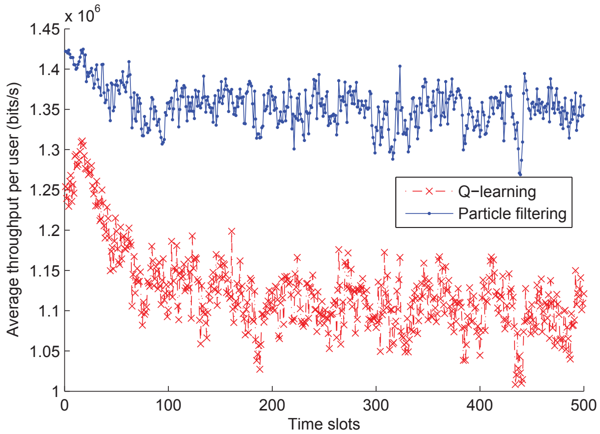

Fig. 1. Comparison between the average throughput when using particle filtering with the case when using Q-learning.

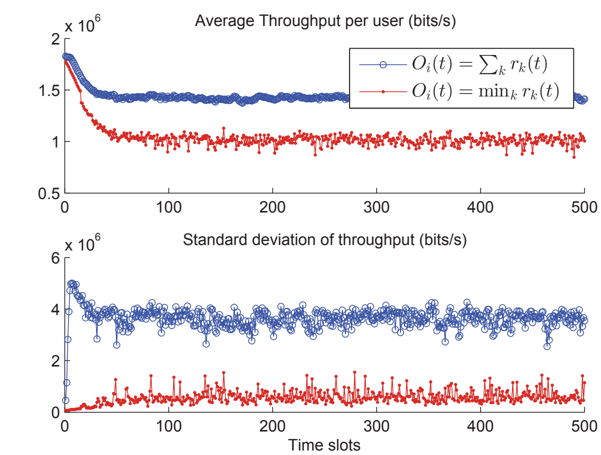

Fig. 2. The average and standard deviation of the throughput when applying particle filtering for different objective functions.

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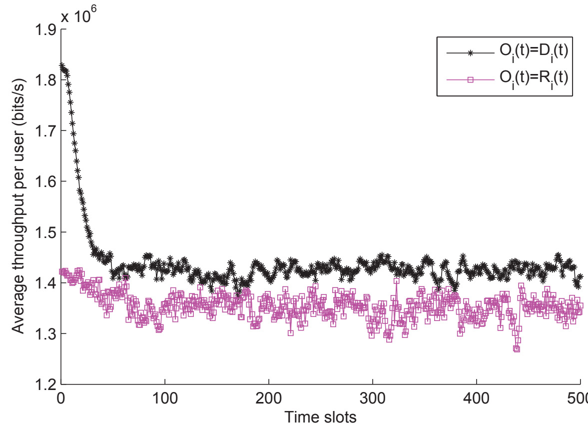

Fig. 3. The achieved average throughput when using difference reward function ($D_i(t)$) with comparison to the intrinsic reward ($R_i(t)$).

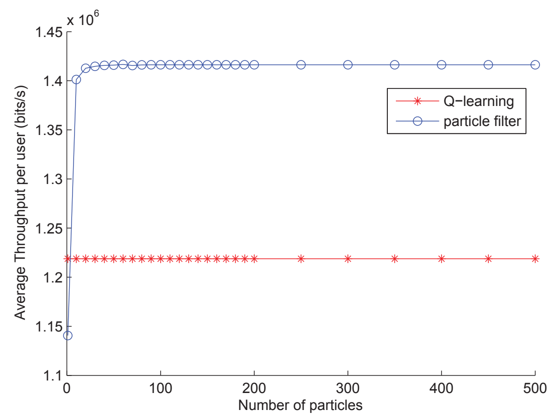

Fig. 4. The achieved reward when applying particle filtering with different number of particles using intrinsic reward.

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